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Application of Support Vector Machines Model in Drought Forecasting Using Standardize Precipitation Index

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ABSTRACT
Drought forecasting is an important aspect of time series forecasting among various researchers the world over using numerous available models to achieve the desired goal. In this study, we have applied the Support Vector Machine (SVM) model to forecast Standardized Precipitation Index (SPI) values involving SPI3, SPI6, SPI9 and SPI12 data series computed for drought forecasting. SVM model is applied to drought forecasting to assess the effectiveness of this model on SPI data series.We,therefore, propose the useof SVM method for modeling SPI data sets. Different inputs of data sets are used for training and testing the SVM models. SPI12 with input12 was found to be the best SVM model with the leastMean Square Error (MSE) of 0.2955, Mean Average Error (MAE) of 0.2139with the highest R of 0.9529 for the training phase. SPI12 with input 4 is the best SVM model with the least MSE of 0.3806, MAE of 0.2881 and the highest R of 0.9313 for the testing phase. The result is an indication that it is better to use SPI12 index for drought forecasting.

Keywords: Drought, SVM, SPI, Time Series, Forecasting

I. INTRODUCTION

Drought forecasting is an issue the world over and has been carried out in various studies by different researchers using different models to achieve their desired goals. There are many natural disasters across the regions such as flooding, earthquakes, droughts etc. hence, the various studies carried out has assisted immensely to prepare for its occurrence or plan for its control. Time series forecasting has been used in a widevariety of scientific applications which includes hydrology where the use of drought forecasting is limited(Mishra & Singh, 2011).Drought monitoring is of crucial importance for freshwater planning and management as well as for prediction of the onset and severity of droughts (Shijin et al., 2012).(Shabri, 2014), described forecasting of drought as a significant tool in management and planning involving water resources in all its systems. In this study, therefore, SVM model is applied in drought forecasting toevaluate the efficiency of the model, Standardized Precipitation Index (SPI) was used on the meteorological analysis of drought at stations where rainfall takes place,since SPI is only the required data on rainfall amount in the study.

In this paper, Support Vector Machine (SVM) which is based on only precipitation data Standardized Precipitation Index (SPI) was applied for meteorological drought analysis. Long term monthly precipitation data were applied. The analysis was carried out on 3, 6, 9 and 12-month long data sets for SPI.

Drought is a natural dynamic phenomenon which can inflict damages and disasters on crops which further results in the loss of yield and by extension affect the life of human beings and animals. The drought has no definite definition, since its occurrence may vary from region to region, hence, its definition is very broad. In this study, we can define drought as a dangerous and unpleasant hard of nature whose impact vary from region to region.Panu & Sharma, (2002) defined drought as scarcity of water which affects adversely various sectors of human society such as in agriculture, hydropower, generation, water supply,and industry. Drought can be categorized as meteorological, hydrological, agricultural and socioeconomic droughts. Panu & Sharma, (2002) see drought as a protracted period of deficient precipitation which results in extensive crop damage that also results to further loss in its

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yields.In the view of Palchaudhuri et al., (2013), drought is a phenomenon which is universally acknowledgedhaving been associated with the scarcity of water and that it is also one of the major environmental disasters that occur in almost all the climatic zones which damages the environment and the economic activities of many countries which increase in frequency and severity.Choubin (2016) described drought as a climatic feature that occasionally takes place. The occurrences of drought pose a serious economic, social and environmental problem,particularly where meteorological and agricultural droughts often occur (Łabędzki, 2016).

Mishra & Singh, (2011) viewed drought indices as quantitative measures which are useful for maintaining droughts and the assessment of their effects. Drought is a natural phenomenon that affects human beings which include animals and it also affectsthe world economy, environment, industries, community and the world's costliest natural disasters which cost global damages annually that affect more people than any other form of natural disasters (Khashei et al., 2003).

According to Dalwadi, (2016), Drought is a regularphenomenon which happensas a result rainfall which is under averagewhich leads to a scarcity of water and economic cost. It is also an unpredicteddrop in precipitation over time and one of the most destructive natural disasters that affect man.The drought has a wide negative effect on agriculture, tourism, water resources, ecosystems and economy (Dai, 2013; Maca & Pech, 2016; Wambua et al., 2014).(Shijin et al., 2012) described forecasting as one of the important research areas in the analysis of the hydrological time series. Raicharoen & Lursinsap (2005) stated that time series forecasting can be termed as the act of predicting the future when the past is understood. Time series forecasting is widely applied, and it becomes an important approach to drought forecasting (Han et al., 2012). (Shah et al., 2010) described time series forecasting as a model which is commonly applied as a wide range of scientific application which includes drought and hydrology.

In the opinion of Cordeiro & Neves (2009), to forecast the future values of time series data is seen as part of time series analysis in where several forecasting approaches have been established and assessed its performance. Zhang, (2013), described the aim of time series forecasting is to estimate future events thatrelied on known past events.The Standardized Precipitation Index (SPI) is a widely used index that characterized metrological drought on a range of timescales. On short-term scales, SPI is closely related to soil moisture while it can be related to groundwater and reservoir storage at a longer time scale. In comparison, therefore, SPI can be compared across regions with different climates.SPI is an index which is normalized andrepresents the likelihood of existence of adetected rainfall quantity when related with the rainfall on a certain location for a long-term. The negative values of SPI represent rainfall deficit and the positive values showa more of rainfall. The standardized precipitation index (SPI) has many characteristics that are upgraded over other indices with its simplicity and flexibility (Shah et al., 2015).Masih (2014), revealed that drought occurs slowly and lasts for a longer period usually more than a season, which has a natural hazard that is a broad and severer impact.Masih et al., (2014)used the SVM method in developing seasonal forecasting models forstandardized precipitation index (SPI). The intention was to assess the performance of SVM in identifyingrepetition of statistical patterns in the differences of meteorological variables in a vast area.

When SVM model is compared with ANN and ANFIS in the drought forecasting using SPI, the SVM model performed better than the others because it gave more accurate values for forecasting (Mokhtarzad, 2017).Ghose & Swain, (2013) and Nayak et al., (2015)identified SVM which is a new machine learning process is claimed as the best model which deals with complex classification problems. Selection of parameter greatly influences the classification accuracy of S SVM and isoften ignored incomparing the experiments, since it consumes timewhich requires understandingof the way SVM works(Núñez et al., 2017).

II. METHODOLOGY

2.1 Time Series Forecasting

Forecasting can be defined as a process in which statements are made about the actual outcome of events which are not yet observed. It is a decision-making tool or planning tool used to help the management or many businesses in its attempt to cope with the uncertainties of the future, relying mainly on data obtained from the past and present and then carry out analysis of the trends.

Shijin et al., (2012) described forecasting as one of the important research areas in the analysis of the hydrological time series. Raicharoen & Lursinsap, (2005) stated that time series forecasting can be termed as the act of predicting the future when the past is understood. Time series

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In the opinion of Cordeiro & Neves, (2009),future values of a time series forecasting is another areas of analysis with where many forecasting techniques have been established andits performances evaluated. Zhang, (2013)described the main motive of forecasting with time series is to forecast future events based on identified past events.

Basic models $X_t = \beta_0 + \varepsilon_t$ (2.11)

Trend models $X_t = \beta_0 + \beta_1 t + \varepsilon_t$ (2.12)

Integrated models $X_{t+1} - X_t = \varepsilon_{t+1}$ (2.13)

2.2 Standardized Precipitation Index (SPI)

The formulation of SPI was by Tom McKee, Nolan Doesken and John Kleist of the Colorado Climate Center in 1993. The aim of SPI is to allocate a sole numeric value to the precipitation that can be compared with different climates across the world.SPI developed by McKee et al (1993) is used in over 60 countries which applied as a drought indicator (Svoboda & Hayes, 2010).

According to (Wu et al., 2001), SPI works as a normalized precipitation using a probability distribution so that values of SPI area standardized from the mean. SPI is an indexbased on the probability of precipitation for any time scale. Normalized distribution allows the estimation of dry and wet periods. A minimum of 30 years of continues monthly precipitation data is needed, however, it is better if it exceeds 30 years(Carrão, 2016).The shortage of rainfall over a period in a place can lead to numerous degrees of condition of drought which affects agriculture and socio-economic activities due to variation of rainfall between different areas which makes drought concept differ from place to place (Van, 2015). Therefore, for more effective valuation of the drought, the World Meteorological Organization WMO, (2010, 2012 and 2015) recommended the implementation of SPI to check the harshness of drought measures.SPI has been applied to measure the shortage of precipitation. Computation can happen at various time scales from 1 to 48 months or even beyond. The computation of time- period relies on the user's application. Short-term SPI can be used to distinguish agricultural drought, and long-term SPI can be used for water sourceand management.

The SPI is a key indicator for drought monitoring used by the (WMO; 2006) and it is widely applied as an operational toolsbyWilhite et al., (2000); Svoboda & Hayes, (2010) and Nielson-Gammon, (2012) and analysis. For example, Lloyd- Hughes,and Saunders (2002) used it to develop a drought climatology for Europe. Santos et al. (2010) examined both the temporal and spatial variability of drought in Portugal using SPI; and Barker et al., (2016) used a regionally aggregated SPI, amongst some indicators, to analyses spatial coherence patterns of drought in Europe.To transform Rainfall to Standard Precipitation Index (SPI), we apply this relation:

$$SPI = \frac{X_{ij} - X_{im}}{\sigma} \quad (2.14)$$

Where:

X_{ij} =average monthly rainfall of a station, X_{im} = average monthly rainfall of all the station, σ = standard deviation

Mean of precipitation value is adjusted to 0, Standard deviation of precipitation is adjusted to 1 and the skewness of the data is adjusted to 0. Having achieved these goals, the SPI is then given as mean = 0 and standard deviation = 1

Mean of precipitation $= \bar{X} = \frac{\sum X}{N}$ (2.15)

The standard deviation of precipitation =

$$S = \sqrt{\frac{\sum (X - \bar{X})^2}{N}} \quad (2.16)$$

In all, N is the no. of precipitation

The existence of SPI over the years has made it possible for its applications with prominent success in the description and monitoring of drought conditions (Almedeij, 2014).

A drought event terminatesas the SPI value attainspositive; drought severity then becomes increasing within the drought duration.

For suitability, the drought severity becomes positive as

$$S = -\sum_{i=1}^{N} SPI_i \quad (2.17)$$

where S is drought severity and *i*begins with the first month and lasts until the conclusion of the drought period N. This relationship proposes that if

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drought continuesit will bring about the worse degree of drought effect(Almedeij, 2014).

2.3 Support Vector Machine (SVM) Model

SVM model was developed by Vapnik (1997) as a means for classification and regression. SVMs is made up of the structural risk minimization principle, while neural networks symbolize the empirical risk minimization principle.SVMs are a useful technique for data classification. SVM is a neural network technology which isbased on statistical learning (Vapnik, 1995).SVMs try to minimize the generalization error and has two main components: support vector classification (SVC) and support vector regression (SVR). Support vector regression (SVR) is used to describe regression with SVMs and has parameters ℂ and Υ (Vapnik, 1997).SVMs are developed from statistical learning theory and have analytically good performance; they are successfully applied in many areas it also solves the classification problem in three different cases namely linear SVM for the separable case, linear SVM for the non-separable case and non-linear SVM (Kumar, 2016).A classification task which usually involves separating the data into training and testing tests according to Hsu et al., (2016) gave each instance in the training set as containing one “target value” which is the class labels and many “attributes” which is the features or observed variables and further stated that the aim of SVM is to yield a model which is on the training and forecastthe marked values of the test data with only the data attributes.

Given a training set of instance-label pairs $\left(x_i, y_i\right)$, i =1, . . . N, the SVM (Cortes and Vapnik, 1995 and Vapnik, 1998) require the solution of this optimization problem:

$$\text{Min } \frac{1}{2} w^T w + \text{C} \sum_{i=1}^{N} \xi_i \quad (2.18)$$

subject to $y_i \left(w^T x_i + \beta\right) \geq 1 - \xi_i$,

$\xi_i \geq 0$

For i = 1,2, …, N,

Where x_i = (1, 2, … N) are the N training points, y_i is the label of each point with values +1or -1 and C is the penalty cost for the sample points which are not correctly classified by the SVM, however, a large C corresponds to a higher penalty to errors.

Generally, SVM models can be divided into four different sets as follows

Classification SVM Type1: - this is known as C-SVM classification

This type of SVMinvolves the training minimization which includes the error function usually given by:

$$\frac{1}{2} w^T w + C \sum_{i=1}^{N} \xi_i \quad (2.19)$$

Subject to the constraints:

$y_i (w^T \phi(x_i) + b) \geq 1 - \xi_i \; and \; \xi_i \geq 0$, i = 1. . . N

C is a constant; w is a coefficient of the vector, b a constant, ξ_i is a parameter for data inputs handling whilei is the index thatlabels the N training cases. $y \in \pm 1$ are the class labels $x_i$being the independent variable.

The kernel transforms the data from the input which is the independent variable to the feature space. It must be known that the larger is the value of C, more error is being penalized. Therefore, C should be chosen with care to avoid overfitting.

Classification SVM Type2: - this is known as nu-SVM classification,

Like classification SVM type1, the classification SVM type2 model minimizes the error function:

$$\frac{1}{2} w^T w - \nu \rho + \frac{1}{N} \sum_{i=1}^{N} \xi_i \quad (2.20)$$

Subject to the constraints

$y_i \left(w^T \phi(x_i) + b\right) \geq \rho - \xi_i, \; \xi_i \geq 0,$ i=1. . . N

and $\rho \geq 0$

In regression, SVM which is the functional dependence of the independent variable x must be estimated. Its assumption is like other problems involving regression, which states that the associationamong the independent and dependent variables are given by a deterministic function f in addition to some additive noise:

$$y = f(x) + noise \quad (2.21)$$

The issue is now to find a functional form f that can correctly predict new cases for SVM. This is realized by training the SVM model on a sample set. This process is like classification and the sequential optimization of the error function. Two types of SVM models can be applicable depending on the definition of this error function. These are regression SVM type1 and regression SVM type2. This continues as follows:

iii. Regression SVM Type1: - this is known as epsilon-SVM regression

This type of SVM uses the error function:

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$$\frac{1}{2}w^T w + C\sum_{i=1}^{N}\xi_i + C\sum_{i=1}^{N}\xi_i^* \qquad (2.22)$$

This is minimized subject to:

$$\left(w^T\phi(x_i)+b\right)-y_i \leq \in +\xi_i$$

$$y_i-\left(w^T\phi(x_i)+b_i\right)\leq \in +\xi_i^*$$

$$\xi_i,\xi_i^* \geq 0,\ i=1,\ldots,N$$

iv. Regression SVM Type2: - this is known as nu-SVM regression

In this type of model, the error function is given by:

$$\frac{1}{2}w^T w - C\left[v\in+\frac{1}{N}\sum_{i=1}^{N}(\xi_i+\xi_i^*)\right] \qquad (2.23)$$

This minimizes subject to:

$$\left(w^T\phi(x_i)+b\right)-y_i \leq \in +\xi_i$$

$$y_i-\left(w^T\phi(x_i)+b_i\right)\leq \in +\xi_i^*$$

$$\xi_i\ \xi_i^* \geq 0, i=1,\ldots,N \in \geq 0$$

The Parameters whichregulator the regression is the cost of error C, the width of the tube $\in$ and the mapping function ϕ .

Kernel Function

Vapnik (1995) stated that any function which satisfies Mercer's conditions can be used as the Kernel function. Currently, the popular kernel functions in machine learning theories are Gaussian kernel or radial basis function kernel (RBF), polynomial kernel, linear kernel,and multilayer kernel. In our study only, RBF is considered and the kernel it is expressed as:

$$K(x_i,x_j) = \exp\left(-\Upsilon\left\|x_i,x_j\right\|^2\right) \qquad (2.24)$$

$\Upsilon > 0$

Where Υ is the parameter of the Kernel.

Hsu et al., (2016) are of the view that SVM requires that each data is represented as a vector of real numbers and if there are categorical attributes they are first converted to numeric data.

III. RESULTS AND DISCUSSION

In this study, the results the precipitation corresponds to the 3, 6, 9 and 12-months data sets used, and their corresponding Standardized Precipitation Indexes (SPIs) computed. The time series for these SPIs values are calculated. The main aimto consider the overall precipitation for the periods of 3, 6, 9 and 12 months was because of the classification of drought to be a short-term,medium-term, and long-term for SPI3, SPI6 and SPI9 and for SPI12 respectively. For modeling, the datawas divided into 80% and 20% used to estimate the model parameters and for the forecast accuracy respectively.To have a good forecasting SVM model, the choice of input variables is important. Five input combinations based on SPI series of previous periods are evaluated to estimate current SPI series which is used for this study.

Table 3.1 showing the results of SVM for SPI3

	Training			**Testing**		
Inputs	MSE	MAE	R	MSE	MAE	R
2	0.7225	0.5588	0.6908	0.6556	0.5068	0.7530
4	0.6433	0.4922	0.7671	0.6026	0.4606	0.7988
6	0.6376	0.4808	0.7723	0.6131	0.4710	0.7944
8	0.6173	0.4552	0.7919	0.6179	0.4637	0.7907
10	0.6091	0.4457	0.8001	0.6253	0.4725	0.7805
12	0.5974	0.4309	0.8116	0.6276	0.4741	0.7810

Table 3.2showing the results of SVM for SPI6

	Training			**Testing**		
Inputs	MSE	MAE	R	MSE	MAE	R
2	0.5091	0.3976	0.8547	0.5178	0.3867	0.8643
4	0.4915	0.3816	0.8663	0.5088	0.3744	0.8706
6	0.4709	0.3542	0.8787	0.5470	0.4096	0.8566
8	0.4249	0.3119	0.9030	0.5398	0.3895	0.8575
10	0.4151	0.3051	0.9083	0.5447	0.4092	0.8516

12	0.4055	0.2947	0.9135	0.5429	0.4041	0.8646

Table 3.3showing the results of SVM for SPI9

	Training			**Testing**		
Inputs	MSE	MAE	R	MSE	MAE	R
2	0.4295	0.3313	0.8979	0.4105	0.3300	0.9169
4	0.4129	0.3197	0.9065	0.4081	0.3278	0.9184
6	0.4003	0.3009	0.9129	0.4079	0.3300	0.9216
8	0.3764	0.2781	0.9237	0.4319	0.3513	0.9131
10	0.3249	0.2399	0.9440	0.4491	0.3528	0.9077
12	0.3188	0.2314	0.9465	0.4665	0.3739	0.9037

Table 3.4showing the results of SVM for SPI12

	Training			**Testing**		
Inputs	MSE	MAE	R	MSE	MAE	R
2	0.3667	0.2872	0.9249	0.3937	0.3027	0.9264
4	0.3565	0.2752	0.9299	0.3806	0.2881	0.9313
6	0.3467	0.2704	0.9339	0.3877	0.2994	0.9298
8	0.3294	0.2486	0.9409	0.3968	0.3101	0.9302
10	0.3132	0.2333	0.9469	0.4194	0.3341	0.9301
12	0.2955	0.2139	0.9529	0.4836	0.3655	0.9173

Tables 3.1to 3.4 gave the various results of the inputs (inputs 2, 4, 6, 8, 10 and 12) for all the Standardized Precipitation Index (SPI3, SPI6, SPI9 and SPI12) computed using the Support Vector Machines (SVMs). The best forecasting model for all the SPIs in both the training and testing phases are input4 and input12 respectively.

Three parameters (C, ε, and γ) were determinedin using the SVM model. These parameters were set to (1, 10) with increments of 1.0 for C and (0.1, 0.5) with increments of 0.1 for ε and γ is fixed as 0.5. The efficiency of the SVM components is obtained by using the relationship between the SPI data series and the SVM coefficient of different levels of decomposition.

Table 4 showing the summary of the best results of theselected SVM models

	Training			Testing		
Data	MSE	MAE	R	MSE	MAE	R
SPI3	0.5974	0.4309	0.8116	0.6026	0.4606	0.7988
SPI6	0.4055	0.2947	0.9135	0.5088	0.3744	0.8706
SPI9	0.3179	0.2314	0.9465	0.4079	0.3278	0.9216
SPI12	0.2955	0.2139	0.9529	0.3806	0.2881	0.9313

IV. FORECAST PERFORMANCE EVALUATION METHODS

The criteria used to decide which model is the best is how relatively the errors are in both the training and testing of the data. This is essential to measure the differences in the amount of estimator from the initial true value. Hence, the selection of the measure with the smallest values as the best.The assessment of the performance of individual model was based on the Mean Square Error (MSE), Mean Absolute Error (MAE) and correlation coefficient (R) used for this study. These means of evaluation performance are generally used in evaluating the outcomes involving time series forecasting (Dawson, Abrahart, & See, 2007). These are stated below: -

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2 \qquad (4.1)$$

$$MAE = \frac{1}{n}\sum_{t=1}^{n}| y_t - \hat{y}_t | \qquad (4.2)$$

$$R = \frac{\sum_{t=1}^{n}(y_t - \bar{y}_t)(\hat{y}_t - \bar{\hat{y}}_t)}{\left[\sum_{t=1}^{n}(y_t - \bar{y}_t)^2\right]^{1/2}\left[\sum_{t=1}^{n}(\hat{y}_t - \bar{\hat{y}}_t)^2\right]^{1/2}} \qquad (4.3)$$

Where $\hat{y}_t$, y_t is the predicted and actual values at time t respectively, while n is the number of Predictions.

V. CONCLUSION

This studyapplied the use of SPI as a drought indicator for the analysis at the stations. since SPI is universally agreed as the most widely applied methods which areconnected to drought forecasting, the accuracy and reliability of estimating the SPI are very significant. The study,therefore, proposes the application of the SVM method for modeling SPI data sets. The SVM models were subjected to training and testingin applying different inputs for SPI3, SPI6, SPI9,and SPI12 data series. SPI12 with input12 is the best SVM model with the least MSE of 0.2955, MAE of 0.2139 and the largest R of 0.9529 with respect to training phase. SPI12 with input 4 is the best SVM model with the least MSE of 0.3806, MAE of 0.2881 and the largest R of 0.931256. this result is an indication that it is better to use SPI12 index for the analysis of drought with respect to this study.

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